Recommendation Method of College English Online Mobile Teaching Resources Based on Big Data Mining Algorithm

Yuhong Xia(✉) and Yudong Wei

Chengdu College of University of Electronic Science and Technology of China, Chengdu 611731, China
hi_xiaxiaxia@126.com

Abstract. The current teaching resource recommendation methods mainly recommend resources according to the relationship between users' historical data and resources, do not consider the timeliness of data, and ignore the attenuation of users' interest in learning resources, resulting in low accuracy and poor recommendation performance. To solve the above problems, in order to improve the accuracy of recommendation of College English online mobile teaching resources, this paper studies the recommendation method of College English online mobile teaching resources based on big data mining algorithm. In the big data teaching environment of College English online mobile teaching, data mining technology is used to mine the characteristics of users' preference for resources. Time information is introduced into the collaborative filtering model integrating neural network to realize the recommendation of teaching resources. In the method test, the recommendation accuracy of the resource recommendation method is 97.26%, and the recommendation performance is significantly improved.

Keywords: Big data mining algorithm · English online teaching · Mobile teaching · Resource Recommendation · Neural network · Collaborative filtering

1 Introduction

The rapid development of science and technology has changed people's way of life and learning. People have changed from traditional classroom learning to today's online learning. The development of educational informatization has spawned a large number of e-learning platforms, so that learners can learn anytime and anywhere, and their learning behavior is no longer limited by factors such as site, time and so on. In the process of mobile learning, client users use smart devices such as mobile phones and tablets to install client software and use wireless networks to interact with the system. The cloud environment of mobile teaching mainly provides services such as device support, computing, network, data storage and so on. With the continuous enrichment of the concept of mobile learning, more and more scholars in the society began to study mobile learning. In the context of the wide application of mobile teaching, resource rich education will

W. Fu and L. Yun (Eds.): ADHIP 2022, LNICST 468, pp. 440–452, 2023.
https://doi.org/10.1007/978-3-031-28787-9_33

be more frequently used in auxiliary teaching than ever before, and major mobile online education platforms will constantly update more teaching resources. With the expansion of user scale and information resources, personalized information recommendation technology will also be widely used in the field of Education [1]. Teaching knowledge information is complex and cumbersome, and the user level is uneven. Only by analyzing the user's knowledge level and knowledge system and recommending relevant courses, can we effectively solve the problem of information resource overload, provide good services for users' mobile learning and increase users' loyalty to the mobile teaching platform [2].

As an important part of educational informatization, network teaching resources are becoming more and more important in promoting the knowledge construction of students and teachers, improving practical ability and developing advanced thinking ability. The high-quality resources on the network are increasing rapidly, but new problems have also arisen: the time of searching resources becomes longer, especially for learners who do not have professional search ability, this kind of problem is more prominent. What's more, it is not sure whether the resources searched are really needed by themselves. Therefore, providing learners with the learning resources they need is one of the ways to solve this problem, and it can also realize personalized learning. If we want to select resources suitable for learners from massive data to realize personalized learning, the traditional search engine can not meet the requirements of personalization. The emergence of recommendation methods provides an effective solution for personalization. The recommendation system does not need users to provide clear needs. It mines users' potential interests through users' historical behavior, so as to actively recommend information that can meet their interests and needs. Although the recommendation algorithm has achieved good results in the field of audio-video and commodity recommendation, teaching resource recommendation has some significant characteristics different from traditional audio-video or commodity recommendation, so the traditional audio-video or commodity recommendation methods can not be directly applied to teaching resource recommendation. Its remarkable feature is that each student user has personalized differences in cognitive ability level, learning habits, learning objectives and other aspects. It can not be recommended only through the user's direct interest similarity like audio and video recommendation, but also according to the student user's cognitive ability level, learning objectives, historical response records, current situation and other personality information. At present, there are many methods about learning resource recommendation, such as the multi task feature recommendation algorithm of the fusion knowledge map of curriculum resources proposed in reference [3]. Based on the end-to-end deep learning framework, the knowledge map is embedded in the task; The high-order relationship between potential features and entities is established through cross compression units between tasks, so as to establish a recommendation model. It realizes accurate recommendation of course resources based on learners' goals, interests and knowledge levels. However, in practical application, this method does not fully consider user behavior, only considers the similarity between information contents, which may also lead to over description and low recommendation accuracy; Reference [4] designs an information-based teaching resource sharing system based on multimedia technology.

In the hardware part, S3C6410 processor is selected to build a multimedia embedded processor, and the hardware interface circuit is designed based on the USB interface board. In the software part, e - R diagram is used to contact the entities of teaching resources, delineate the attributes of information-based teaching resources, build databases with different functions according to different processes of sharing teaching resources, and set a data supplement program in the database to finally realize resource recommendation and sharing. However, this method will automatically expand the scale of clustering, make clustering fuzzy, and the recommendation effect is insufficient.

In order to improve the accuracy of recommendation, this paper proposes a recommendation method of College English online mobile teaching resources based on big data mining algorithm. Build a big data teaching environment for online mobile teaching of College English; Using data mining technology to mine users' preferences for English resources; It creatively introduces time information into the collaborative filtering model based on integrated neural network to complete the recommendation of teaching resources. The experimental results prove that the contribution of this method is to solve the shortcomings of existing mobile teaching resource recommendation, improve the accuracy of Learning Resource Recommendation and the effect of mobile teaching.

2 Recommendation Method of College English Online Mobile Teaching Resources Based on Big Data Mining Algorithm

2.1 Build a Big Data Teaching Environment for College English Online Mobile Teaching

The fundamental purpose of College English online mobile learning is to break the time and space constraints of the traditional classroom, and the traditional web page centralizes the management of teaching resources with the help of information technology. Then, through the Internet, users can access these teaching resources for learning with the help of smart phones, tablets, laptops and other intelligent terminal devices connected to the Internet. Mobile teaching is divided into five teaching theories: informal teaching, context teaching, Situational Cognition, experience teaching and activity teaching. The teaching methods of informal teaching are mainly reflected in unconsciously obtaining information, content and communicating and discussing with people. The characteristic is to teach to any object anywhere. Context teaching is based on learners' knowledge structure, learning interest and learning motivation to provide the basis for mobile teaching. Situational cognitive teaching emphasizes the influence of environment on learners' teaching. This theory believes that meaningful teaching can occur only when teaching is embedded in a specific environment. Experience teaching emphasizes thinking and practice. Learners can improve their learning efficiency only through continuous thinking and practice and applying the experience summarized after practice to the subsequent practice process [5]. Activity teaching refers to teaching in activities, focusing on a certain problem, discussing, teaching, practice, activity design, etc. It mainly advocates active teaching and defines the purpose of teaching. According to the characteristics of mobile teaching and the teaching requirements of College English, when carrying out college English online mobile teaching, the mobile teaching platform needs to build a good learning environment for students with the help of big data technology. When students conduct College English online mobile learning, they not only need to interact with teachers through the mobile teaching platform, but also need the platform to meet the needs of students for resources, learning strategies, learning paths and learning emotion regulation in the teaching process. Figure 1 shows the structure of big data teaching environment for College English online mobile teaching.

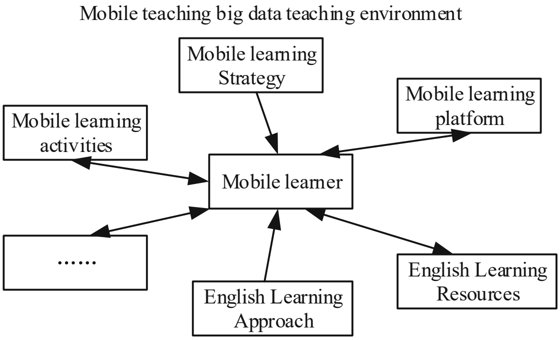

Fig. 1. Online mobile teaching big data teaching environment

Traditional personalized learning will give learners a fixed learning path and provide fixed learning resources, without fully considering learners' autonomy. The learning environment in the context of big data is no longer a closed space. Taking learners as the center makes learners have the right to choose the learning content, gives learners enough space, makes learners have a sense of control and achievement in learning, realizes personalized learning through the choice of learning path and learning content, and enables learners to explore more fields of learning content when they complete their learning easily and happily, Expand knowledge and improve self-efficacy. Personalized learning students supported by big data are no longer isolated learners. They can form learning communities and online virtual learning interest groups in various interpersonal networks. Learners can discuss and exchange with each other and share learning experience. The interaction between learners and others can improve learning efficiency and reduce learning loneliness [6]. The personalized English learning environment built under the background of big data pays more attention to learners' emotional attitude, and the evaluation and diagnosis of learners are more humanized. The emotions for learners are divided into six aspects: boredom, enthusiasm, confusion, frustration, happiness and surprise. Emotional attitude will have varying degrees of impact on the learning process. A pleasant mood is more suitable for completing learning, and boredom is not conducive to completing learning, Through the capture of learners' emotional attitude to assist the current learning diagnosis and resource recommendation, when students show emotional burnout, give positive encouragement mechanism in time to prevent learners from giving up learning halfway. Through the diagnosis of learners' different emotional states, analyze students' interest and preference for College English teaching resources, so as to improve the accuracy of resource recommendation.

2.2 Mining User Preferences for College English Resources

Big data provides technical support for the construction of College English online mobile personalized teaching environment. It can mine the characteristics of teachers, analyze the needs of teachers, predict the behavior of teachers, and make it possible to teach students according to their aptitude. Creating a personalized teaching environment can bridge the boundaries of personal teaching space and teaching space. The construction of personalized teaching environment highlights the characteristics of network teaching in the new era. The personalized teaching environment based on big data can support teachers to carry out independent, individualized and creative teaching, and provide teachers with personalized teaching space based on their own teaching experience. The behavior data generated by the teacher in the teaching process are summarized into the teacher database, and the data mining technology is used to analyze the teacher's behavior data and modify the teacher's static teaching model, so as to form the teacher's dynamic teaching characteristic model. The construction and modification of dynamic teaching model is the core of real-time teaching model construction. Dynamic teaching model studies the behavior data generated by teachers in the teaching process. The behavior characteristics of teachers are invisible information, which does not need the deliberate expression of teachers. The system can automatically collect the data generated in the teaching process, such as the retrieval content of teachers, teaching progress, discussion in the teaching process, etc. In order to make the transition from static teaching model to dynamic teaching model, it is necessary to collect learners' dynamic behavior data and analyze and summarize them through data mining technology and behavior analysis technology.

The cluster analysis technology in data mining is used to locate the teaching level, teaching interest, teaching style, teaching ability and other groups with common teaching aspirations. A large number of dynamic data are more and more accurate for the analysis of teachers, more and more accurate positioning, and more personalized resource recommendation services are provided. If you want to get accurate interest bias, you first need to extract user features, and then judge the polarity of the user's bias towards a feature. According to the characteristics of College English online mobile teaching, this paper puts forward the following seven characteristic dimensions, namely, learning time and learning times, average length of each learning, frequency of viewing course announcements, weekly investment time, frequency of viewing course calendar, fixed degree of daily learning time and fixed degree of learning time interval, and constructs the preference model of mobile learning users [7].

Ontology based model representation has strong expansibility and good adaptability, but the construction of ontology is mainly affected by researchers' knowledge and experience. Especially when the definition domain is large, the effectiveness of ontology construction is difficult to guarantee; Although vector space model is not the best user requirements description method, its good universality makes it the most extensive and mature user model construction method. Therefore, the combination of the two is still used for user preference modeling in this study.

Generally, the representation methods of user interest modeling include keyword list representation and scoring matrix representation between user and project. The former is to extract the keywords of user interest and establish the user interest model based on the keywords. The latter uses the user's score on the project to directly reflect the user's interest in the project. These two methods are easy to understand in use, but they tend to be coarse-grained in interest division. For users' fine-grained interests and the weights of different interest categories, they can not be deeply mined. We need to convert the text data into binary data that can be recognized by the computer. In this paper, a vector space model representation method will be used to solve the above problems. In text classification, it is assumed that simple keywords and sentences can be used to represent the target text. Based on this assumption, vector model can be used to represent the target text, in which vector elements are keywords and sentences of College English teaching resources text.

In the vector space model, the user set is represented by the letter Y as $Y = \{y_1, y_2, \cdots, y_m\}$, and the element set of the user English learning preference model is represented by H as $H = \{h_1, h_2, \cdots, h_n\}$. Where y_i represents the i users, with a total of m users; h_j represents the j element, and there are n elements in total. The user's preference for each element is recorded as the preference weight value ω_{ij}, which represents the weight value of the i user's preference for the j element. The weight value of this study is expressed by Likert five level scale.

In order to provide learners with the required and appropriate personalized learning resources more accurately, we need to et the learning preference of the target learners from the learners themselves, and calculate the learners' learning preference from the three dimensions of learners' knowledge state, online learning participation and resource score. With the decline of students' interest, students' short-term learning interest preference gradually tends to 0. Therefore, the user preference matrix becomes very sparse. User learning preferences are influenced by both short-term learning interests and long-term learning interests. This paper introduces ontology when constructing the learner preference model, and excavates the students' preference characteristics for resources according to the user preference ontology of College English mobile learning shown in Fig. 2 [8].

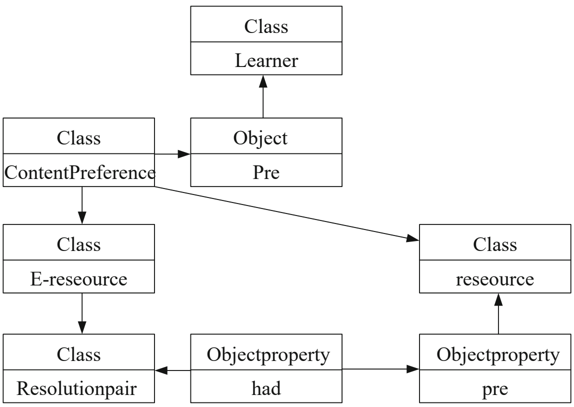

Fig. 2. Schematic diagram of the user's English learning resource preference ontology

According to the above content, the big data clustering mining method is used to mine users' preference characteristics for College English resources. It is assumed that the center of each cluster is c_z and the internal distortion of this class is $\sum \varphi^2(x_i, c_z)$. Here, $\varphi^2(x_i, c_z)$ represents the distortion measure between two data points. Therefore, for all cluster $\{J_c\}_{c=1}^k$, its overall performance can be expressed in the following form:

$$Q = \sum_{c=1}^{k} \sum_{x_i \in J_c} \varphi^2(x_i, c_z) \tag{1}$$

In order to make the weight obtained in the clustering process obey the given feature preference F as much as possible, a penalty term is added to the above objective function to reflect the possible violation of preference. Therefore, for each feature preference tuple $f = \{s, t, \delta\} \in F$, the penalty term is defined as $\max\{\delta - \omega_s + \omega_t, 0\}$. Now, for each preference, m auxiliary variables are introduced to form vector $\gamma = [\gamma_f]$, so as to form the following characteristic preference penalty term:

$$\begin{aligned} &\min \sum \gamma_f + \eta \\ &s.t. \begin{cases} \omega \in \Delta_d \\ \omega_s - \omega_t \geq \delta - \gamma_f \\ \gamma_f \geq 0 \end{cases} \end{aligned} \tag{2}$$

Among them, tuple $\{s, t, \delta\}$ represents the user's preference for College English learning resources. The tuple represents that the importance of feature s is at least δ than feature t, that is, $\omega_s - \omega_t \geq \delta$ and δ are numbers greater than 0, and their values can be automatically adjusted or predetermined in method training. η is the preference penalty parameter; d is the dimension of preference characteristics.

In addition to the given feature preference a priori, we do not want to make unfounded assumptions on other aspects of feature weight to cause over fitting. Therefore, the negative entropy term $-H(\omega)$ is introduced into the objective function and minimized to ensure that the weight is as smooth or balanced as possible. The more balanced the weight, the greater the value of $H(\omega)$, and vice versa. For the convenience of calculation, the entropy used in this study is:

$$H(\omega) = 1 - \omega^T \omega \tag{3}$$

Among them, maximizing entropy is equivalent to minimizing $\omega^T \omega$. In order to establish the local weight clustering algorithm of feature preference, the distance measurement of the clustering algorithm is calculated according to the following formula:

$$\varphi^2(x_i, c_z) = \sum_{j=1}^{d} \omega_{jc} D_{ic}^j \tag{4}$$

Where D_{ic}^j represents the distance between sample point x_i and cluster center c_z on the j feature. The weight of clustering dependence satisfies $\sum_{j=1}^{d} \omega_{jc} = 1$. ω_{jc} is the weight of feature j corresponding to cluster c.

In fact, the distance measures can be defined differently according to the different characteristics of the dataset, with the common Euclidean distance used in this paper. The cluster distance between the behavioral data and the teaching resources is calculated, and the characteristics of the users' preference for college English resources are extracted.

2.3 Realize the Mobile Teaching Resource Recommendation

According to the preference characteristics of users for College English resources mined above, this study adopts the collaborative filtering model of neural network to realize the recommendation of College English online mobile teaching resources. In a neural network, the nodes of each layer will convert the input data into output, and then enter the next node. How to convert the output of the upper layer node into the input of this layer node requires a functional relationship to convert. The so-called activation function refers to this functional relationship, which maps the input of neurons to the output through the activation function. The neural collaborative filtering framework is mainly divided into four layers: input layer, embedding layer, neural collaborative filtering layer and output layer.

The input layer is responsible for the input of users and items, and converts each user and item into n vector. If there are n users, the n users will be converted into the vector of $1 \times n$, which will be converted into a sparse vector. After the input enters the embedding layer, multiply the input vector by the embedding matrix f. If there are n users and the embedding dimension is m dimension, the size of the embedding matrix is $m \times n$, and the row represents the embedding vector of the user preference resource. In order to prevent neuron inactivation, this paper uses prelu activation function in the framework of collaborative filtering model of fused neural network. Prelu activation function adds parameter α on the basis of relu function, which is very small. When $\alpha = 0$, prelu will degenerate into relu function.

$$F(x) = \begin{cases} x_i, x > 0 \\ \alpha x_i, x \le 0 \end{cases} \tag{5}$$

Loss function is mainly responsible for calculating the difference between the actual value and the predicted value, according to the difference, to evaluate the error between the predicted value and the actual value, by constantly to narrow the difference, to train the model, so as to get a better effect, in general, the smaller the loss function, the performance of the model will be better. In the neural network model, mainly for the current teaching resources recommendation algorithm is not fully mining the effective implicit feature information design, its main purpose is through the neural network in different dimensions of teaching resources depth mining, at the same time, through the output layer of nonlinear transformation seamless into the joint probability matrix decomposition.

To input the feature vectors yf and ef of users and College English mobile teaching resources into multi-layer neural network to get the final score, it is necessary to connect the user's preference feature vector and the feature vector of mobile teaching resources for input. The output layer is mainly responsible for nonlinear mapping of the output of the previous layer. Therefore, it is necessary to project in the d dimensional space of the joint probability matrix decomposition model to complete the recommendation task.

In real life, user preferences will change over time. Take the time information into account in the recommendation algorithm to better find user preferences. Compared with other recommended objects, the curriculum resource recommendation model constructed in this paper will be greatly affected by time. With the advance of time, the curriculum resources are constantly updated and changed. The content direction of a user to learn at each stage is different, and the user's learning interest will also change with the change of time. The older the courses, the courses that users don't often watch at this stage, the less recommendable they will be to users.

In order to meet the requirements that users' interests change with time, recommend effective teaching resources to users more accurately. In this paper, time factor is added on the basis of neural collaborative filtering algorithm. After unsupervised classification of time information through K-means, the effect of recommendation is improved by adding time information.

Record the mobile teaching information data set, the establishment time of each course, the user viewing time, and the current time, and then calculate the user's relative viewing time for each college English course as time information.

$$T = \frac{T_y - T_e}{t - T_e} \tag{6}$$

Where, T_y is the latest viewing time of mobile teaching users, T_e is the course upload time, and t is the current time.

In terms of time, the closer the user has seen the course, the greater the time information the new course will get. In the process of model training, with the increase of the number of network layers, the convergence speed of training may slow down. Batch standardization can use some standard means to pull the distribution of input values of each layer of neural network back to a certain standard. In this way, the whole training speed can be accelerated. In this paper, batch standardization layer is added to MLP model to speed up the training speed, It can also further alleviate the problem of over fitting. After completing linear learning and nonlinear learning, the obtained potential feature vectors are connected together and output through the activation function. After using the training sample set to train the parameters of the collaborative filtering model fused with neural network, the relevant data of mobile learning users are input into the recommendation model with the determined parameters. After the model processing, the recommendation results of College English online mobile teaching resources are obtained. Based on the above theoretical content, the research on the recommendation method of College English online mobile teaching resources based on big data mining algorithm is completed.

3 Resource Recommendation Test

In the context of the wide application of mobile teaching, the above studies the recommendation method of College English online mobile teaching resources based on big data mining algorithm. This section will test the recommendation performance and effect of the recommendation method of teaching resources.

3.1 Test Preparation and Scheme Design

In this test, the crawler program is used to collect data from a college English mobile teaching platform, and a total of 318860 pieces of data are crawled. Each data information includes the ID of the College English course, the establishment time of the course, the user's ID, the user's viewing date, the user's score of the course, etc., and the data is saved in courses_ and_ users. CSV file to facilitate the subsequent training of the model. In order to get better experimental results, this paper also processed the data as follows. In the crawled data, the user viewing time information and course establishment time information are strings containing "year", "month" and "day". In order to ensure the unity of subsequent data input and facilitate the application of data sets, it is necessary to process the crawled user viewing time information and course establishment time information. Change the form of string into the form of number. At this time, the viewing data is not the date with month, year and day, but a string of numbers. In this paper, the gettimestamp () method is defined through the def function in Python language. Through this method, all the date formats in the data are converted to the time stamp format, which is convenient for the next step. In the process of data analysis, in order to obtain a more accurate experimental result and reduce the impact of inconsistent units of experimental indicators. In this paper, the indicators are standardized and then put into use. These indicators are changed into numbers without units, which can be better compared or weighted, which lays a foundation for subsequent experimental analysis.

In order to prove the recommendation effect of the College English online mobile teaching resources recommendation method based on big data mining algorithm, this paper selects the data crawled and processed according to the above content as the data set. Because some users have too few course records, conduct unified screening before the test, and select the data with more than 50 course learning records for random selection. Finally, 7712 users and all college English online courses in the data set were randomly selected as the data set, and trained under explicit feedback and implicit feedback respectively for experimental evaluation.

The test adopts the form of comparison to ensure the scientific and credible test data. The multi task feature recommendation algorithm (reference [3]) and the resource sharing system based on Multimedia Technology (reference [4]) are taken as comparison method 1 and comparison method 2, respectively, and compared with the teaching resource recommendation method studied in this paper. The experimental indicators are the recommendation accuracy, recall and F-score of teaching resource recommendation methods to evaluate the recommendation effect.

3.2 Test Results

Table 1 shows the comparison of the recommendation accuracy and recall rate of the three resource recommendation methods when recommending teaching resources to different numbers of mobile university English learning users.

By analyzing the data in Table 1, we can see that the accuracy and recall rate of the teaching resource recommendation method based on big data algorithm studied in this paper are higher than the other two recommendation methods. At the same time, with the increase of the number of users, the accuracy of recommendation results is gradually

Table 1. The accuracy and recall comparison of the recommended methods

Number of users	Teaching resource recommendation method based on big data algorithm		Comparison method 1		Comparison method 2	
	Accuracy rate /%	Recall/%	Accuracy rate /%	Recall/%	Accuracy rate /%	Recall/%
10	97.47	90.24	86.78	80.44	85.66	79.63
20	97.36	87.82	89.15	81.45	83.66	77.36
30	96.63	88.45	85.57	83.88	84.31	78.55
40	95.82	90.87	85.13	79.90	85.05	78.41
50	96.98	89.73	84.68	81.96	84.28	75.48
60	96.59	89.59	84.91	83.61	84.17	77.09
70	96.94	89.14	88.03	80.92	83.03	78.84
80	97.06	90.06	86.46	81.43	84.95	78.87
90	97.37	89.27	86.12	80.76	82.04	77.61
100	97.44	89.49	87.51	81.01	81.92	76.46
110	96.96	88.15	89.24	78.86	81.18	77.45
150	96.38	87.83	86.49	80.97	80.82	77.79
200	98.92	90.02	87.43	81.54	80.01	75.62
300	98.33	90.11	86.97	79.95	79.72	76.98
500	98.65	88.86	84.56	82.81	79.63	78.60

stable. From the average recommendation accuracy of the recommendation method, the average recommendation accuracy of this method is 97.26%, and the average recall rate is 89.31%; The average recommendation accuracy rate of comparison method 1 is 86.60%, and the average recall rate is 81.30%; The average recommendation accuracy rate of comparison method 2 is 82.70%, and the average recall rate is 77.65%. The above data shows that the recommended accuracy of this method is at least 9% higher than that of the other two comparison methods.

Figure 3 shows the comparison of F-score values of three resource recommendation methods.

It can be seen from the curve trend in Fig. 3 that the F-score value curve of the method in this paper is always above the F-score value curve of the other two methods, indicating that the recommended performance of the method is more stable.

To sum up, the recommendation methods of College English online mobile teaching resources based on big data mining algorithm in this paper are better than the traditional methods, and the accuracy, recall and F-score are improved. It shows that the method in this paper can predict learners' preferences relatively accurately when predicting

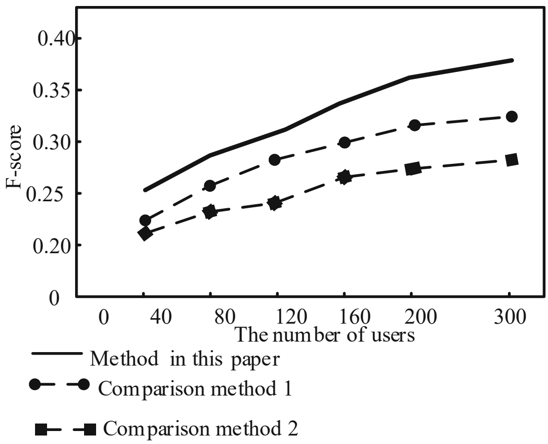

Fig. 3. Comparison of F-score values of recommended methods

learners' preferences for learning resources, and mobile teaching users are more satisfied with the resources recommended by the method.

4 Conclusion

With the continuous progress and development of online education platform, teachers' teaching mode is no longer limited to teaching based and book knowledge, and students' access to knowledge is no longer limited to classrooms, libraries and teachers. Mobile teaching extends the traditional classroom teaching to after class and after class. At present, the existing teaching methods in mobile teaching are relatively single. Each teacher can only obtain teaching resources through active teaching methods such as search, which can not be understood by analogy. However, with the development of educational big data, educational resources show the characteristics of massive resources, information overload and uneven quality, which makes teachers face the problems of information overload and knowledge loss. Therefore, it is necessary to provide more types of teaching resources for teachers, and recommend the contents they may be interested in as far as possible, so as to draw inferences from one instance. This paper proposes a recommendation method of College English online mobile teaching resources based on big data mining algorithm, and tests the recommendation method. The test data of recommendation method show that this method improves the teaching effect and promotes students' teaching on the basis of improving the accuracy of recommendation of teaching resources. The recommendation method of College English online mobile teaching resources based on big data mining algorithm proposed in this study has certain research value in the research and application of College English Education Resource Recommendation. However, due to the limited conditions, the recommendation method of this paper mainly studies to improve the accuracy of resource recommendation, and the improvement of recommendation efficiency is not obvious. Future studies can improve the efficiency of recommendations by ensuring their accuracy.

References

1. Yu, H., Sun, L.: Accurate recommendation algorithm of agricultural massive information resources based on knowledge map. Compute. Simul. **38**(12), 485–489 (2021)
2. Wu, H., Xu, X.: Knowledge Graph-assisted multi-task feature-based course recommendation algorithm. Comput. Eng. Appl. **57**(21), 132–139 (2021)
3. Shi, Y., Zhang, J.: Design of information-based teaching resources sharing system based on multimedia technology. Modern Electron. Tech. **44**(20), 32–36 (2021)
4. Jin, Y., Chen, H.: Value orientations, realistic limitations and effective strategies of big data mining for education. Theor. Pract. Educ. **41**(19), 3–8 (2021)
5. Xie, Y.: Analysis model simulation of multidimensional data de-clustering algorithm based on big data mining. Tech. Autom. Appl. **40**(12), 112–115 (2021)
6. Wang, Z., Liang, J.: Research on the rapid recommendation model of online teaching resources in colleges and universities. Inform. Stud.: Theor. Appl. **44**(05), 180–186 (2021)
7. Zhong, Z., Shi, J., Guan, Y.: Research on online learning resource recommendation by integrating multi-heterogeneous information network. Res. Explor. Laboratory **39**(09), 198–203 (2020)
8. Wang., G., Yuan, H., Huang, X., et al.: Recommendation algorithm for e-learning resources based on improved collaborative filtering. J. Chinese Comput. Syst. **42**(05), 940–945 (2021)